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Price Impact of Block Trades: The Curious Case of Downstairs Trading in the EU Emissions Futures Market

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Using high-frequency data from the European Climate Exchange (ECX), we examine the determinants of price impact of €21 billion worth of block trades during 2008-2011 in the European carbon market. We find that wider bid-ask spreads and volatility are characterised by smaller price impact. Larger levels of price impact are more likely to occur during the middle of the trading day, specifically the four-hour period between 11am and 3pm, than during the first or final hours. Purchase block trades induce relatively smaller price impact on price run-up, while sell block trades exhibit larger price impact on price run-up. We conclude that block trades on the ECX induce less price impact than in equity or conventional futures markets, and that a significant proportion of the effects contradict findings on block trades in those markets; thus, we provide the first evidence of the curious bent to block trading in the EU Emissions Trading Scheme (EU-ETS).

Keywords: Carbon futures; Block trades; Price impact; High-frequency trades; European Union Emissions Trading Scheme (EU-ETS); Determinants; Liquidity.

JEL Classifications: G12, G13, G14, G15, G18

1. Introduction

The Kyoto Protocol, an international agreement aimed at curbing global greenhouse gas emissions, came into force on 16 February, 2005. Using 1990 emission levels as a threshold, it requires a combined reduction of 5.20% in greenhouse gas emissions by industrialised countries. About 141 countries, accounting for more than 55% of global greenhouse gas emissions, ratified the treaty by 2004. The greenhouse gas permit trading market has since grown into a multi-billion dollar market, with Europe at the forefront. The European emissions permit market, through the EU's main climate change policy instrument, the EU Emissions Trading Scheme (EU-ETS), has accounted for more than 80% of global market share in each year since 2006. In 2010, the value of total EU Allowances (EUAs) – carbon credits – traded climbed to US$ 119.8 billion (more than 84% of the global carbon market value), and the EU-ETS-driven share of the global carbon market increased to 97% (Linacre,

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Kossoy, and Ambrosi 2011). Futures account for more than 70% of the Euro value of trades, with trades executed either OTC or on organised exchanges. The European Climate Exchange (ECX) in London is the largest of the exchanges in the scheme and in the world, with more than 90% of EU-ETS exchange-based trading share.

Since the EU-ETS was established for the purpose of reducing emissions in industrial installations, a significant proportion of trades on the platforms are institutional (most institutional trades are executed as blocks). Municipal and state government-led initiatives are already established in other countries, such as China, Canada, Japan and the United States. Finally, the Conference of Parties held in Durban in December 2011 reached an agreement to negotiate a successor to the Kyoto Protocol by 2014. This raises the strongest prospect yet of global compulsory emissions trading. The EU-ETS will be the logical anchor for a global scheme. Our study therefore contributes to both global climate change policy formulation and the finance literature on block trading.

This study is motivated by the fundamental necessity to understand the impact of the increasingly large number of block trades in the EU-ETS exchange-based futures trading. In 2005, approximately 80% of EU-ETS derivatives trades occurred OTC; most of these trades meet the ECX's definition of block trades. The volume traded OTC progressively decreased to average approximately 70% of the total transaction value over the entire course of Phase I, the trial period (2005-2007). By January 2010 (during Phase II, the Kyoto commitment period: 2008-2012), the proportion of exchange-based trades in the scheme had reached 50%, according to World Bank estimates (see Kossoy and Ambrosi 2010). This development is driven by the need of participants to avoid counterparty risks, an issue that has taken on greater significance in derivatives markets as a whole.

The price impact of block trades has been extensively researched for equity markets, and recently for futures markets (see Chou et al. 2011). Kraus and Stoll (1972) were the first to demonstrate the price impact of block trades. They present several arguments as to the cause of this phenomenon: short-run liquidity effects occurring as a result of price compromise suffered because counterparties are not readily available; price compromise when instruments are not perfect substitutes for each other, leading to inefficient trading and hence price impact; and the idea that price concessions granted in order to execute market order underscores *desperation* to execute the market order. These factors convey information to markets about the potential value of the order to the counterparties, and hence the order becomes information driving, leading to price impact. Holthausen, Leftwich, and Mayers (1990) find evidence of premium payment or price concession in the execution of buyer-initiated block trades. They hold that buyers pay a premium prior to a block trade; the premium is consequently incorporated permanently into the price, while no evidence of premium payment is found for block sales. Kraus and Stoll (1972) find that price impact is higher for block purchases than sales, because a concession or implicit commission is usually higher for purchases than sales, suggesting that there is indeed a premium paid on block sales. A major contribution of their pioneering work is the establishment of a positive relationship between block trades and price impact. Chan and Lakonishok (1993), among others (see for example Barclay and Warner 1993, Holthausen, Leftwich, and Mayers 1990), provide supporting evidence for this; they also find a relationship between market capitalisation and price impact (see also Chan and Lakonishok 1995).

Holthausen, Leftwich, and Mayers (1987) also investigate price impact due to block trades, and discover that larger trades induce larger price impact than smaller trades. Barclay and Warner (1993), Chakravarty (2001) and Alzahrani, Gregoriou, and Hudson (2013) also provide evidence that order size and subsequent execution potentially result in corresponding trade price impact. In relation to temporary price impact, the first study to show asymmetry in block trades' price effects is Gemmill's (1996) on the London Stock Exchange, with significant differences in the magnitude of price impact being reported. Gemmill (1996) reports permanent price impact due to block trades on the London Stock Exchange, and a permanent impact equivalent to 33% of the bid-ask spread for block trades that are purchased, and 17% for block trades that are sold.

Consistent with Gemmill (1996), most of the studies conducted on the price impact of buyer- and seller-initiated block trades report price impact asymmetry between the two groups (see among others Conrad, Johnson, and Wahal 2001, Keim and Madhavan 1996, Chiyachantana et al. 2004, Holthausen, Leftwich, and Mayers 1990, Chou et al. 2011). They generally submit that prices appreciate after purchase block trades are executed, and depreciate on their sale. The depreciation that occurs after sell trades are executed suffers reversion, but purchase block trade induced appreciation remains. Chan and Lakonishok (1993) argue that the reason for this is that block sales have a higher likelihood of involving a broker (acting as an intermediary) than block purchases. The temporary impact from sell trades is therefore a reflection of price concession as compensation for the role played by the broker. Liquidity thus plays a key role in the existence of price impact asymmetry between block purchases and sales (see also Gregoriou 2008).

However, despite the large body of literature on price impact of block trades in the conventional markets, to our knowledge, no study has been undertaken for block trade price impact in permit markets. We therefore attempt an analysis of determinants of price impact in the EU-ETS using tick data from the scheme's largest platform, the ECX, in order to understand the impact of block trades in this important market. Our results show intriguing patterns that are largely inconsistent with earlier studies from traditional markets. For permanent and temporary effects, we find several instances of price impact asymmetry for block purchases and sales. Contrary to previous literature on equity markets, wider spreads lead to smaller price impact. We attribute our findings to the fact that block trades executed after a price run-up induce smaller price impact, as suggested by Saar (2001). The implication is that liquidity concerns in the EU-ETS play a less prominent role in emissions permits pricing than in customary markets. This is supported by Ibikunle, Gregoriou, and Pandit

(2013), who find that small amounts of trading lead to larger proportions of price discovery in the EU-ETS. Short-run improvements in liquidity, though an important factor in market efficiency (see Chordia, Roll, and Subrahmanyam 2008), do not detract from block trade price impact on the world's largest carbon platform. Our findings have implications for compliance traders and policy makers alike. It is important that in designing future phases of the EU-ETS, this and other aspects of our results are considered.

The remainder of this paper is structured as follows. In Section 2, we provide a discussion of the EU-ETS mechanism and the setup of the ECX, and review related literature based on permit trading. Section 3 outlines the data and econometric methodology used. Section 4 discusses the empirical analysis, and Section 5 concludes.

2. Background of Study

2.1. Institutional Set-up

The EU-ETS currently covers about 12,000 installations within the European Union (EU), Liechtenstein, Norway and Iceland. The initial aim was to fulfil the EU's obligation under the Kyoto Protocol. Although the terminal year for the Protocol is 2012, the EU has already extended the scheme into a third phase since the start of 2013. Since its inception in 2005, the scheme has steadily improved in terms of market structure and functioning. The scheme runs as a classic cap and trade, with emission permits initially 100% grandfathered in 2005. Subsequently, certain percentages have been allocated for sector-dependent auctioning. In the EU-ETS, the emission permit is known as the European Union Allowance (EUA). EUAs are electronically generated records on the national registries of individual participating countries. The national registries are all connected to a common central location called the Community Independent Transaction Log (CITL). Every April, the installations submit EUAs equivalent to their verified emissions for the preceding year. Project-based permits can also be submitted;

with certain restrictions[1] (see Daskalakis, Ibikunle, and Diaz-Rainey 2011 for a financial perspective of the EU-ETS).

We are not aware of any study on the price impact of block trading in the EU-ETS; however, Mizrach and Otsubo (2014), in a general microstructure analysis of the EU-ETS, examine the price impact of regular EUA and CER trades. No distinctions are made for the trades based on size or trade sign. They also do not distinguish between upstairs and downstairs markets trades, which we separate in this study. Benz and Klar (2008), Frino, Kruk, and Lepone (2010) and Ibikunle, Gregoriou, and Pandit (2012) examine liquidity, price discovery and transaction costs in the EU-ETS. Their results are not directly relevant to this study, but do provide an insight into vital microstructure properties of the EU-ETS. Some other studies have examined off-platform variables that can explain price formation in the EU-ETS: Christiansen and Arvanitakis (2005), Mansanet-Bataller, Pardo, and Valor (2007) and (2008), all using daily data, investigate the effects of energy fundamentals on daily EUA returns during Phase I of the EU-ETS. Mansanet-Bataller and Pardo (2007) and Miclăuş et al. (2008) employ event study methodology in investigating the effect of NAP and emissions verification announcements on EUA prices. Ibikunle et al. (2012) provide the longest time-horizon study of the EU-ETS to date; they argue that the ECX has experienced accelerated improvement in market efficiency and liquidity over the 2008-2011 period, the first four years of the Kyoto commitment phase. This view is also held by Kalaitzoglou and Maher Ibrahim (2013) and Ibikunle, Gregoriou, and Pandit (2013), whose analyses show evidence of improving market maturity and trading sophistication.

2.2. The European Climate Exchange (ECX) and Trading Rules

The ECX, a member of the Climate Exchange Plc. group of companies, is the largest carbon exchange in the world by volume and value. Trading rules and procedures on the exchange follow general financial markets practice. Trading commences at 07:00:00 and lasts until

17:00:00 UK local time. There is a pre-trading period of 15 minutes from 06:45:00 to allow members to place orders in preparation for the start of trading; however, almost no orders are executed during this period. The settlement period, which runs from 16:50:00 to 16:59:59 UK time, is the third stage of the trading day and is used to determine the settlement price. The fourth stage of trading is the after-hours period, reserved only for reporting Exchange for Physical/Swaps (EFP/EFS) trades. Ibikunle, Gregoriou, and Pandit (2013) have analysed the contribution of trades reported during this period to price discovery. These trades can be regarded as a form of upstairs trading in the context of the ECX, and hence will not be examined in this paper.

Trading occurs both directly on the platform and bilaterally off it, before being submitted to the exchange for on-screen registration. By virtue of this, the exchange maintains three trading mechanisms: trades occur on the ICE platform; by EFP/EFS trades; or through the Block Trade Mechanism. Participants submit orders by being entered into the ETS. The trades executed as a consequence of orders are deemed to be anonymous according to exchange rules. The executed trades go via the trade registration system (TRS) for account allocation. Price transparency is ensured by the availability of real-time prices made available on ICE Platform screens and vendor sources. These vendors include Bloomberg, CQG, E-Signal/FutureSource and Reuters. The exchange also sets reasonability limits for purchase and sale orders. A purchase (sale) order above (below) the limit is rejected. A sale (purchase) order above (below) the limit is accepted without being executed, but the market shifts to alter the reasonability limits, hence placing it within the limit. The exchange also maintains a 'no cancellation range', within which trades reported as mistakes may not be cancelled. This rule enhances market confidence and reduces noise trades. Clearing is provided by Ice Clear Europe, which charges transaction fees (in addition to annual subscription fees for various participant categories) on behalf of the exchange. Transaction fees are not placed on the exercise of an option or on physical delivery of futures contracts. The minimum tick has been held constant at €0.01 per tonne of CO_2 since 27 March, 2007, from its previous rate of €0.05 at commencement in 2005.

3. Data and Methodology

3.1. Data

We obtain two sets of data; the first is high-frequency data from ICE Futures Europe, detailing intraday transactions to the nearest second. The dataset covers the start of Phase II of the EU-ETS (1 January, 2008) to 9 May, 2011. The use of the dataset ensures that this study provides the longest time period analysis of EU-ETS Phase II trading to date. The second dataset contains end of day (EOD) variables; it is also from ICE Futures Europe, and covers the same time span and provides daily aggregates of our intraday data, among other daily variables. We select only December expiry contracts because they are the only ones for which official exchange index data are available; this is perhaps because a sufficient level of trading only occurs in December maturity contracts. The selected December maturity contracts are for 2008, 2009, 2010, 2011, 2012 and 2013. This phenomenon in the EU-ETS is well reported, and researchers have focused mainly on December maturity contracts (see for example Kalaitzoglou and Maher Ibrahim 2013, Ibikunle et al. 2012 among others). All trades executed within the initial pre-open period and during the after-hours market are excluded. All other trades executed off-market and in the upstairs market, which includes mainly EFP/EFS trades, are also excluded. These steps and our chosen methodology are adopted to provide a basis for comparing our results with previous studies. Finally, we exclude the December trades for contracts approaching maturity given the observation of extreme levels of volatility relative to other months, which might bias our estimates. Thus, for a futures contract with December 2010 maturity, the last trade included in the final sample will be its last trade in November 2010. The final dataset consists of a total of 961,131 trades over the period. We follow the ECX's definition of a block trade as any trade with a minimum lot size of 50 contracts (50,000 EUAs). This definition yields a sample size of 16,715 block trades (excluding EFP/EFS trades). This is about 1.74% of the total number of trades in the cleaned dataset. The absolute quantity is comparable to the 16,951 NYSE downstairs block trades analysed by Madhavan and Cheng (1997) for 30 Dow Jones stocks, and larger than the sample of 5,987 from the London Stock Exchange investigated by Gemmill (1996). We adopt the trade signs allocated to each trade by the ECX in our data set.[2]

3.2. Methodology

We begin our inquiry by computing three types of price impact generally recognised in the literature. These are the temporary, permanent and total price impact measures. The microstructure literature acknowledges permanent price impacts as those induced by private information, and temporary price impacts as those resulting from noise or liquidity-induced trading, leading to reversal of price (see Glosten and Harris 1988, Chan and Lakonishok 1995, Easley, Hvidkjaer, and O'Hara 2002).

Usually, block trades demand more liquidity than is likely to be available at current quoted prices. Thus, if a block trade is to be fully executed against the available level of liquidity, it must ‘walk’ through the order book, and as a result ends up forcing instrument prices to shift in the trade direction; i.e. down for sells and up for buys. The temporary impact on price measures the market’s frictional price reaction to the execution of a block trade, which also dissipates thereafter, hence the definition represented in Equation (1) below. Specifically, Equation (1) quantifies the liquidity element of price impact since the block trade will be executed at a price different from the equilibrium price as dictated by current quotes. This friction in pricing occurs because of the absence of readily available willing counterparties that can take the opposite side of the block trade at the best available corresponding quote. The temporary effect can thus be viewed as compensation to the counterparties providing the liquidity required for block trade execution. The compensation is offered by block purchasers (sellers) as a price premium (discount) in order to entice counterparties into trading with them.

The permanent impact encapsulates the *enduring* impact of the block trade on an instrument, i.e. the price shift that is not reversed following the block trade. Thus, the permanent impact measures the information component of a block trade, since the previous price equilibrium is not reverted to. This implies that the market has learnt something new about the instrument, which leads to a new price equilibrium. In this study, we follow Holthausen, Leftwich, and Mayers (1990), Gemmill (1996), Frino, Jarnecic, and Lepone (2007) and Alzahrani, Gregoriou, and Hudson (2013) in using the five-trade benchmark to compute the price impact measures; the equations used are also based on these papers. Thus, for temporary impact (Equation 1), we measure the percentage of price reversal after five trades following the block trade; and for permanent price impact, Equation (2) considers the percentage change in price from five trades prior to the block trade to five trades after the block trade. The third price impact measure, total impact, captures the entire percentage price impact, which includes both the liquidity and the information component. Since we project (in line with previous studies stated above), that the liquidity effect dissipates only after about five trades, Equation (3) should capture both the temporary and permanent price effects of the block trade. We ensure comparability by calculating all three measures as percentage returns according to Equations (1), (2) and (3):

$$\text{Temporary Impact} = \frac{(P_{t+5} - P_t)}{P_t} \tag{1}$$

$$\text{Permanent Impact} = \frac{(P_{t+5} - P_{t-5})}{P_{t-5}} \tag{2}$$

$$\text{Total Impact} = \frac{(P_t - P_{t-5})}{P_{t-5}} \tag{3}$$

We use transaction prices in the absence of direct quotes.[3] We adopt the model of Frino, Jarnecic, and Lepone (2007), thereafter employed by Alzahrani, Gregoriou, and Hudson

(2013), in examining some likely determinants of block trade price impact on the ECX. Accordingly, we estimate the following time series regression with EUA contracts-specific variables:

$$PI_t = \gamma_0 + \gamma_x X_t + \gamma_2 \sum_{i=1}^{9} TD_i + \gamma_3 \sum_{i=1}^{4} DD_i + \gamma_4 \sum_{i=1}^{11} MD_i + \varepsilon_t \tag{4}$$

where PI_t corresponds to one of three price impact measures: total price impact, permanent price impact and temporary price impact. The explanatory variables are computed as follows. $\boldsymbol{X_t}$ is a vector of six explanatory variables (Size, Volatility, Turnover, Marketreturn, Momentum and BAS) defined below. TD_i, DD_i and MD_i are dummy variables for time (hour) of day, day of week and month of year and are further defined below.

Size represents the natural logarithm of volume of contracts contained in the block transaction.[4] Based on the assumption that trade size corresponds to information content (see Kraus and Stoll 1972, Easley and O'Hara 1987, Chan and Lakonishok 1993 among others), we adopt trade size as a proxy for information content of the block trade. When investors have private information about an instrument, they act based on the new belief developed as a result of the new information. Hence, they place a sell order if the belief is that the instrument is overpriced, or purchase if the instrument is under-priced (see also Madhavan, Richardson, and Roomans 1997). *Volatility* represents the standard deviation of trade execution price returns for the trading day up until the block trade.[5] This measure is in line with previous studies (see for example Frino, Jarnecic, and Lepone 2007). Volatility is representative of intraday fluctuation in trading prices; it shows the pattern of trading belief over the course of a trading session, and can therefore be regarded as an implicit proxy of adverse selection costs of trading. The higher the level of volatility of an instrument, the greater the risk associated with it, thus leading to wider spreads as compensation for trading (see Sarr and Lybek 2002). The onset of larger spreads on account of volatility suggests that volatility will lead to price impact. It is expected that volatility of the futures contracts will be positively related to price impact (Domowitz, Glen, and Madhavan 2001).

Turnover represents the natural logarithm of the aggregate Euro value of all futures contracts traded on the trading day prior to the execution of the block trade, divided by the prevailing Euro volume of open interest. Turnover has been regularly employed as a measure of trading activity and market liquidity (see among others Lakonishok and Lev 1987, Hu 1997, Frino, Jarnecic, and Lepone 2007). Further, open interest has been established as a component of market liquidity measures in futures markets. Using open interest as a component of the proxy for market depth (liquidity) follows Bessembinder and Seguin (1992) and Fung and Patterson (1999). Open interest is a reflection of the order flow of trades and the readiness of traders to risk their funds, and therefore has similar levels of correlation with volatility that spreads have. Price impact is expected to be lower with improvements in liquidity; hence, we anticipate a negative relationship with price impact.[6] *Momentum* is computed as the lagged cumulative daily return for each contract over five trading days before the trading day of the block trade. This expresses the trading trend for the specific instrument. Higher returns will indicate a purchasing trend, and lower returns, a selling trend. Saar (2001) argues that the price performance history of an instrument is related to its expected price impact asymmetry. Specifically, block trades that are executed on the back of decreasing price performance will manifest higher positive asymmetry, and block trades executed after a strong run of price appreciation should exhibit less impact, or possibly negative asymmetry. Since the transition to Phase II in the EU-ETS, the market has experienced stronger liquidity and market efficiency, and hence has largely been on a run-up in terms of price performance. Based on this, we anticipate momentum will have predominantly negative price impact coefficients.

BAS is a second measure of liquidity in the model. Relative bid-ask spread is the prevailing relative bid-ask spread when the block transaction is executed. We expect that when spreads are wide, there would be higher price impact than when they are narrow. We compute relative bid-ask spread as the last ask price prior to the block trade minus the last bid price before the block trade, divided by the midpoint of both prices. *Marketreturn* is the contract-specific daily return on the ECX EUA index for each contract. By adopting contract-specific return we emulate Frino, Jarnecic, and Lepone (2007) in using a more refined measure of market return. Alzahrani, Gregoriou, and Hudson (2013) and Frino, Jarnecic, and Lepone (2007) report intraday effects for block trade impact. Thus, for consistency, we introduce trading hour, day of week and month of year dummy variables in order to capture trading time/period effects. For these sets of dummies, the last trading hour (16:01-17:00), Friday and December are employed as references. The use of December as a reference month is important given that the contracts in our sample all have December expiries.

4. Results and Discussion

4.1. Descriptive Statistics

Panel A in Table 1 shows descriptive statistics based on trade classification. Of the 16,715 block trades in our final sample, 8,356 are buyer-initiated and 8,359 are seller-initiated. The total volume of block trades to the total number of trades in the sample is 1.74%. In comparison to conventional markets, trading in a permit market like the ECX seems to be less dependent on institutional activity. However, this is only true if we equate block trading activity to institutional activity. The nature of the EU-ETS is such that emissions are capped and traded in the upstream; hence, trading in EU-ETS permits is dominated primarily by both installations trading for compliance purposes and other institutional investors, such as Barclays Capital. However, most institutional trading occurs OTC and in the upstairs market. While comprising only a small portion of EUA trades on the ECX, institutional trades account for a far higher proportion of the Euro volume of the exchange-based trades (see Mizrach and Otsubo 2014, Ibikunle, Gregoriou, and Pandit 2013). 0.869% of all the trades in the final sample are identified as buyer-initiated block trades, while a marginally higher percentage of 0.87% are seller-initiated block trades. This trend, while conforming to some previous studies(for example Frino, Jarnecic, and Lepone 2007), contrasts with others (see for example Gregoriou 2008).

[INSERT TABLE 1 HERE]

After removing the high-volume EFP/EFS trades from the on-screen block trades, we have a total of 16,715 block trades with a combined value of approximately €21 billion. For all block trades, the average number of contracts per trade is more than 13 times the value of all the trades combined (both block and non-block). The average number of trades (transaction value) for block purchases is higher than sales, at 80.21 (€1,258,030) and 77.67 (€1,207,400), respectively. The average relative bid-ask spread value is 0.067% for purchases and 0.056% for sales. The average relative bid-ask spreads for *all trades* compare favourably with those of all block trades. With the exception of block purchases, the spread for all trades is higher than all classes in Table 1. For more developed markets and traditional asset classes, the expectation would be to have reduced spreads for all trades and larger spreads for block trades, since they are more likely to be influenced by private information rather than the search for liquidity. A number of microstructure studies suggest that large-sized trades are more informative than smaller ones (see Easley and O'Hara 1987 for further details). Investors have been known to fragment trades over a period of time in order to take advantage of private information rather than execute an *abnormally* large trade; they do this in order to avoid revealing the privately held information before they can take advantage of it. To some extent, the results in Table 1 showing block purchases with a higher average number of contracts per trade seem to confirm this intuition. It is also noted that *all trades*, which is approximately 11 times smaller than the average block trade, has a slightly higher average relative spread. A possible explanation is the noisy nature of price discovery during the trading day on the ECX. Noise in the price discovery process and information asymmetry on the ECX have been documented by Ibikunle, Gregoriou, and Pandit (2013). In any case, the statistics presented in Table 1 are not by themselves conclusive evidence of noise in our data. Also, if noise is synonymous with trading on a platform, we must ensure that the data are representative of this fact; results presented in Section 5 will provide clearer insights.

4.2. Regression Results and Discussion

4.2.1. Price impact and trade sign

We investigate the determinants of price impact of block trades for all, purchase, and sell transactions separately in this section; Table 2 shows the results. Size coefficient estimates for sell block trades are all highly statistically significant and negative. The coefficients confirm that larger sell block trades have both permanent and temporary impacts on the price of carbon futures on the ECX, implying that the larger the block trade, the bigger the negative sell block trade impact. The temporary effects, however, contradict expectations, since price should fall after a sell trade; further analysis examines this curious relationship. There are further and substantial instances of this relationship evident in the results given in Table 2. On the one hand there is sufficient evidence to show that block trades on the ECX induce statistically significant price impact; on the other hand, these impacts do not conform to the established literature stream for conventional markets. For example, the total effects of block purchases are negative and statistically significant for all of Volatility, Marketreturn, Momentum and BAS. The corresponding total effects coefficients for combined block trades are also negative and statistically significant for all of those variables, with the exception of Volatility. This implies that purchase block trades dominate the direction of block trade impact, since the sell block trade total impact coefficients are mostly positive. However, only a fraction of the values obtained support this conclusion. It is misleading to focus on the total price impact estimates, since it is difficult to tell which of the two key impact types (liquidity/temporary and information/permanent) is predominant. For clarity, we examine the temporary and permanent impact estimates in Table 2. Here, the block purchase price effects are more in keeping with existing literature. For example, the positive (and statistically significant) temporary effects Volatility, and Marketreturn estimates for the purchase trades are consistent with theory and the current literature (see for example, Alzahrani, Gregoriou, and Hudson 2013, Chiyachantana et al. 2004).[7] The literature suggests that increased depth (Turnover) reduces block trade price impact. Our results imply that this is only supported for purchases in the case of total price impact. Temporary effects estimates for both purchases and sales suggest that for liquidity-induced trades, market depth does not dull trade impact; the direction of impact remains consistent. Only the block sale coefficient is significant for permanent effects, contradicting Frino, Jarnecic, and Lepone (2007), but supporting Alzahrani, Gregoriou, and Hudson's (2013) work on the Saudi Stock Market (SSM). Alzahrani, Gregoriou, and Hudson (2013) suggest that huge block sell trades in actively traded instruments may signal adverse information about the intent of the trades, since they indicate beliefs of informed participants and consequently lead to an increase in instrument sales. This can lead to intensification of the price impact of the block trades involved.

Positive Marketreturn coefficient estimates indicate larger price impact for purchase block trades, and reduced impact for block sell trades; results obtained are largely in keeping with this expectation. Consistent with Frino, Jarnecic, and Lepone (2007) and Alzahrani, Gregoriou, and Hudson (2013), they are positive for the full range of price effects for the block sell trades. The permanent effects and temporary effects estimates for the purchase trades are positive as well. According to Chiyachantana et al. (2004), institutional block trades executed on the back of price appreciation lead to lesser permanent price impact. This corroborates Saar (2001), which reports that block trades executed following a recent price run-up generate smaller price impact. The total effects Momentum coefficient estimates show statistically significant results. The total effects coefficient estimate for purchase block trades is negative and significant, indicating lesser price impact as a result of price run-up. The negative and statistically significant sell coefficient (total effects) implies the opposite trend holds for sell block trades. The statistically significant BAS estimates (purchase: total effects; sell: total and permanent effects) imply that with wider spreads, there is reduced price impact for both purchase and sell trades, and thus with narrower spreads, there is greater price impact. This contradicts previous studies (see for example Aitken and Frino 1996, Gemmill 1996). The ECX is a platform created for trading emission permits, unlike equity markets aimed at trading stocks. Emission permits are designed to be submitted only once a year, but the market remains very liquid all year round since the commencement of Phase II of the EU-ETS (see Montagnoli and de Vries 2010, Ibikunle, Gregoriou, and Pandit 2013). Trading emission permits when they are not immediately needed for submission indicates a level of informed trading. Based on this reasoning, high levels of liquidity may not necessarily inhibit price impact for block trades. The BAS estimates support those obtained for the Turnover variable.

[INSERT TABLE 2 HERE]

Buyer- and seller-initiated block trades on the ECX induce both temporary and permanent price impacts. Increased liquidity also generates a larger price impact. The dissimilarities in market properties between the EU-ETS cap and trade scheme and traditional financial markets is underscored by the differences in the impact of the two liquidity measures used in the model. Evidence also confirms the prediction that there is reduced price impact for both purchase and sell block trades when an instrument is on a price run-up prior to the block trade execution.

4.2.2. Intraday variations in price impact

In conventional markets, it has been reported that spreads conform to a U-shaped pattern over the trading day. However, little has been reported on intraday variations in the EU-ETS.

Rotfuβ (2009) reports a roughly U-shaped pattern of intraday volatility on the ECX using ECX data from the first year of trading in Phase II (2008). Ibikunle, Gregoriou, and Pandit (2013) report a slightly different inverted S-shaped intraday pattern of volatility and trading volume using data from the same platform. To our knowledge, the only available evidence of intraday variations in estimated spread pattern available for the EU-ETS is the work of Ibikunle, Gregoriou, and Pandit (2013). The authors, using the Huang and Stoll (1997) spread decomposition model, obtain half-spread estimates for several trading intervals on the ECX; they depict a kind of U-shaped evolution of intraday half-spread. Figure 1 shows intraday variations in the average relative bid-ask spread, computed by using our entire dataset (including non-block trades). There is a discernible suggestion of a U-shaped pattern emerging.

[INSERT FIGURE 1 HERE]

In order to examine the presence of intraday variations in the intensity of block trade price impact for the ECX, we introduce intraday dummies for each trading hour, and the results are also presented in Table 2.[8] The intervals are as defined in Section 4, and Table 2 also contains the relevant results. Results suggest that block trades executed during some intervals of the trading day generate price impacts, which are significantly different from those, generated by trades executed during the last hour of the day. The middle of the trading day, between 11am and 3pm, shows a propensity for inducing a larger sell block price impact than the last hour of the trading day. The difference in the effect of intraday trading activity patterns on the ECX and other traditional financial platforms is underscored by this behaviour. Some studies show that the first hour of trading has been reported as the period when block trades induce the largest price impact (see Frino, Jarnecic, and Lepone 2007 as an example). Earlier in this section, we report that, contrary to earlier studies, wider spreads in fact characterise less price impact on the ECX. This result is therefore the only logical outcome of our investigation of time of day effect. This is because Figure 1 shows that the lowest spreads are experienced during the middle of the day, and the highest spread intervals happen during the first hour of the trading day. There is, however, some evidence of price impact asymmetry, since some of the block purchase coefficients are negative and significant. This trend suggests that during the 4th, 5th, 8th and 9th hours of the trading day, block purchases induce less total price impact than for the last hour of the trading day. Further examination of the results shows that for temporary effects, which proxies the liquidity component of price shifts, there is no evidence of the price impact asymmetry observed for total effects. This set of results underscores the observation of Ibikunle, Gregoriou, and Pandit (2013) that the last hour of trading on the ECX is dominated by informed trading and thus is likely to exhibit larger levels of permanent price impact due to new information being impounded into the prices. This is because the final trading hour is largely dominated by purchase traders; this also explains the price impact asymmetry with block sells.

4.2.3. Day of the week and Month of the year effects

We compute and compare mean price impact measures for each day of the week and each month of the year. We observe weak but significant differences in price impact in the day of the week analysis. This leads us to expect some level of price impact variations on account of trading day, hence the decision to include day of the week dummies in Equation (4) The month of the year analysis yield stronger evidence of significant differences, therefore we also include month dummies in Equation (4); December, the delivery month for all the futures used in this study, is employed as the reference month. Results presented in Table 2 suggest that while there are some statistically significant differences in the price impact of block trades on account of trading day of the week, these are restricted to block purchases only and only exist in the case of total effects. Further, the level of statistical significance is generally weak. Thus, we document another instance of price impact asymmetry on the basis of block trade type.

Table 2 also presents the results for the month of year dummies. The results are quite interesting: we observe strong price impact asymmetry between block purchases and sells. For total effects, all 11 sell block month dummies are statistically significant, and eight are for permanent effects. None of the purchase block month dummies meet the conventional level of statistical significance. Cases of observed price impact asymmetry between trade types are quite common in microstructure literature; in the conclusion to this paper, we attempt an explanation of this phenomenon as it applies to this unusual market. The results obtained for block sells strongly suggest that the price impact for sell block trades is highest in December. Since we eliminate December trades for maturing contracts from our sample, this is expected. The elimination of the December trades of the contract closest to maturity means that December trades may be relatively less volatile than trades in the other months of the year. The Volatility coefficients in Table 2 suggest that there is reduced price impact with increasing volatility in the market. Thus, other months, being relatively more volatile than December, would experience less sell block trade impacts.

4.2.4. Trade size dependencies on price impact

Microstructure studies suggest that liquidity-influenced trades are characterised by small orders, and informed trades by larger orders (see Glosten and Harris 1988 as an example). Ibikunle, Gregoriou, and Pandit's (2013) analyses of the large orders that dominate the after-hours session on the ECX indicate a confirmation of this proposition in the European carbon futures market. If different types of trades are characterised by differing sizes of trades, it is suspected that block trades will not uniformly induce price impact. To determine how block trades of different sizes can affect price functioning, we adopt the approach of Alzahrani, Gregoriou, and Hudson(2013) and Madhavan and Cheng (1997) in dividing block trades in our sample into three different trade size categories. We divide block trades into three groups, as follows: 50,000-100,000 EUAs (small), 100,001-200,000 EUAs (mid) and >200,000 EUAs (large). Equation (4) is estimated for the three groups using all three measures of price impact.

[INSERT TABLE 3 HERE]

Table 3 reports the results for purchase block trades. The first observation we make is that of a very high proportion of small block trades. Approximately 90% of executed trades in the sample are for small blocks. Another observation is the dearth of estimates significantly different from zero. Also, the results are largely consistent with Table 2, especially for the small blocks, since they dominate the sample. However, a few observations deserve mention. As stated earlier, positive market return induces greater permanent price impact; there is now further evidence that this is linked to trade size. The large purchase block trades on average effect 26.26% more permanent price shifts when market return is positive than the small purchase block trades; this is because larger trades convey more information to the market. Conversely and expectedly, owing to the fact that temporary price impacts are composed of liquidity effects, the small purchase block trades cause on average 78.28% more temporary price shifts than the large trades. It is also noted that the large coefficient estimate for temporary effects is not even significantly different from zero.

We also observe that the larger blocks, especially the mid-size blocks, potentially induce higher price impact, in line with theory, than smaller sized ones. For example, consider the Volatility variable, which measures the dispersion of participants' belief, its (Volatility) total effects estimates for all three trade sizes are statistically significant. The coefficient of the mid-size blocks is positive and statistically significant, and also higher than the other groups at 1.44. This means that for this group, increasing volatility leads to higher price impact. The negative and statistically significant coefficients for the small and large blocks imply that increased volatility does not necessarily imply higher price impact; it instead signals the opposite. This is consistent with earlier total effects coefficient estimates for purchase block trades from Table 2. Since these two groups account for more than 93% of the sample size, the consistency with earlier results on purchase trades is not surprising, but the mid-size blocks estimate is consistent with theory. The total effects coefficient estimates for Momentum are statistically significant for all three sizes; again the results suggest that mid-size blocks induce higher price impact on a price run-up, as reported by Frino, Jarnecic, and Lepone (2007), while results on the other two sizes confirm the argument of Saar (2001) and results in Table 2. The negative and statistically significant coefficients confirm that less price impact is induced on a price run-up.

Differentiation (outright dominance) of the mid-size blocks group from (over) the largest blocks category is consistent with the hypothesis and evidence presented by Barclay and Warner (1993) after testing block trade price impacts on NYSE stock prices. In their sample, most of the cumulative stock price change is due to medium-sized trades. Here, the interesting pattern evolving may be an indication of 100,000 EUAs becoming the threshold for price impact effects. Already, we show that the small blocks induce more temporary than permanent price impact, thus implying that most of the trades in this group are liquidity seeking. This, coupled with the large volume of small blocks of 50,000 EUAs, suggests a gradual erosion of the market's view of a 50,000 EUA-worth trade as a block trade. The ECX sets the standard for what is regarded as a block trade, and currently it stands at 50,000 EUAs, according to exchange rules. Markets have, however, been known to induce structural shifts in response to emerging trading *culture*. The ECX, as an EU-ETS platform, is a product of political action and may not be subject to the same expectations as regular markets developed as engines of wealth creation. Even still, the market seems to be gradually taking on a life of its own. This, however, does not explain why the largest block category shows fewer price impact effects than the mid-size category. Barclay and Warner (1993) argue that under certain conditions, informed traders, rather than trading in large sizes, would usually split up their trades into smaller chunks that fall into the medium-sized category, hence the asymmetric phenomenon. Also, we suggest the following: the frequency of on-screen purchase block trades >200,000 EUAs on the ECX (3.45%) over three years and four months is very low. The low frequency levels may be a contributing factor to the low coefficient estimates. Perhaps infrequent trade sizes are likely to induce less price reaction than those that are fairly regular. Further, in our dataset, more than 98% of the large blocks occur outside of the first hour of the normal trading day. The total effects coefficient for the mid-size category indicates that greater price impact occurs during the first hour of the trading day for this group of trades. Therefore, since trades during the other periods in the day are less likely to induce price impact than those executed during the first hour, the effects of the large blocks may have been consequently muted by a general reduced price reaction to such trades during the other periods of the normal trading day. The R^2 values for the equation estimations range from 2.32% to 24.84% for total effects estimates, which is an indication of the significant explanatory power of the model, especially for the large block trades. This further evidences their informativeness.

[INSERT TABLE 4 HERE]

Table 4 shows the results for sell block trades. We observe trends similar to those in Table 3, with approximately 91% of executed trades in the sample made up of the small blocks. Also, as in the purchase estimates, there is a dearth of coefficients that are significantly different from zero. Like the purchase block results, the results in Table 4 are consistent with sell blocks estimates in Table 2. However, unlike with the purchase blocks, the small sell blocks contribute more to the direction of price impact observed in Table 2 than the larger blocks. The only exception seems to be for temporary effects due to volatility, which is principally driven by the mid-size blocks. The negative and statistically significant value of the mid-size blocks shows that increased volatility results in higher price impact for midsize blocks. The opposite is the case for the small and large blocks. Consistent with Alzahrani, Gregoriou, and Hudson (2013), the significant total effects coefficient for the small blocks is larger than for the larger sizes. This indicates that smaller sized sell block trades are more informative than larger ones. Professional traders have long been known to split large block trades into smaller trades to avoid early detection of their information content (see Barclay and Warner 1993, Chakravarty 2001). Although microstructure studies show that informed trades are discernible also from the direction and frequency of trades, trades fragmentation potentially mutes the price impact of block trades (Keim and Madhavan 1996). The permanent effects coefficients for Marketreturn seem to support this view; thus, there are larger price impacts for the small sell blocks, as they are perceived as being more informative.

Another interesting set of results to note in Table 4 is the fact that Momentum coefficients are negative all through, consistent with Table 2. When viewed in tandem with the block purchase estimates in previous tables, we can argue that block purchase trades behaviour on the ECX is largely consistent with Saar (2001) (cumulative lagged returns reduce price impact), and that of sell block trades with Frino, Jarnecic, and Lepone (2007) (larger price run-ups lead to larger price impact). The time-related dummies results are qualitatively similar to sell blocks estimates in Table 2. The R^2 values are generally larger than for previous regressions, with the model being more fitted to explaining price impact for the large sell blocks; the R^2 values range from 20.89% to 25.17% for the largest sized sell blocks. The general trend exhibited in Table 4 suggests that sell block trades executed on the ECX on the whole are less likely to induce price impact than purchase block trades.

5. Conclusion

The key finding of this study is that the price impact of block trades in emissions permit markets is largely different from the price impact of block trades in conventional financial markets, with emissions permit markets experiencing generally lower price impact than traditional financial markets. Block trades increasingly constitute large Euro volumes of trades in the EU-ETS, as more installations try to avoid counterparty risks by trading on platforms rather than OTC; in any case, most OTC trades are registered on exchanges to avoid such risks. Our study therefore is of significance to CFI traders and exchange operators alike. By examining the determinants of block trades, we improve understanding of the impact of larger than regular trades on an environmental platform. This understanding is useful for regulators and exchange operators, and it will contribute to the development of market design considerations. For example, for purchase blocks, we find little evidence of large impact for ECX block trades within the threshold of 50,000-100,000 EUAs and above the threshold of 200,000 EUAs; instead, the impact is stronger for the mid-size blocks between 100,000 to 200,000 EUAs. This suggests a disparity between the platform operator's expectation of price and trading dynamics, and the view of the market participants.

Results show that most of the block trades on the ECX occur at the minimum quantity for the exchange-sanctioned block trade size of 50,000 EUAs. This is consistent for both buyer- and seller-initiated block trades; it also indicates that traders on either side of block trades on the ECX employ identical trading tactics in terms of order placing. The evidence suggests that stealth trading is a strategy being employed by most block traders on the platform. The low volume of block trades – 16,715 (1.74%) out of a total of 961,131 trades in our final sample – also suggests that hitherto block trading intentions may have been executed by splitting aggregate large orders into traded quantities below the block trade threshold of 50,000 EUAs. This suggestion is reinforced by the nature of the EU-ETS, where most participants are either big compliance traders or institutional investors, who are expected to be trading in large quantities. In comparison with conventional instruments, the price impact of carbon futures on the ECX is small and largely statistically insignificant. Lack of price reaction to large trades can be viewed as a possible consequence of thin trading (see Ball and Finn 1989). Although trading has advanced in the EU-ETS, it remains very low in comparison to established markets. Since there is little price reaction, there is very little opportunity to benefit from price shocks. We find some proof of price impact asymmetry for buyer- and seller-initiated block trades. Some results also suggest that sellers pay a premium, rather than buyers, on buyer-initiated trades, which clearly contradicts many studies. However, it is not surprising that sellers rather than buyers pay a premium on the ECX when the market structure is considered. The ECX is a derivatives exchange for emission permits, which are required for submission only once a year; hence, for most trading days the permits are largely hedging instruments. Compliance buyers do not need to hold on to the underlying instruments all year round and therefore only need to take long positions in the market to ensure that they are insulated against penalties for non-compliance. In the event that they are in possession of excess instruments, they can undertake a short position. Considering that the permits hold little value to a compliance trader unless they are being submitted, many may make concessions to sell them even when the trade is buyer-initiated, and such a realisation may trigger the buyer's interest in the first place.

This paper also provides evidence that lower price impact is characterised by wider spreads. For buyer-initiated block orders, trade execution induces larger price impact in the ECX during the middle of the trading day than during the first and last trading hours. We find evidence in support of positive price run-up leading to both lower price impact and higher price impact, depending on the trade sign. For block purchases, there is smaller price impact when a trade occurs after a price run-up; for block sales, there is greater price impact. There is, however, also a block trade size dependency to this, as shown in Section 5. In many cases, the most information-laden trades are not the largest ones, but the medium (for most purchases) and small (for most sells) trades. Policy makers must therefore ensure that regulations in the emissions markets keep pace with trading innovations. Our findings also have implications for the participants in the EU-ETS who must trade in emissions instruments for the purpose of compliance. This class of participants is more likely to trade in large blocks; thus, our findings can inform their trading strategies. Specifically, the dissimilarities to conventional platforms that we document in this paper underscore the need for trading re-orientation to attain a required level of trading sophistication in the market. The message is clear: this market has a rather curious bent.

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Notes

1. Project-based permits include Certified Emission Reduction Units (CER) and Emission Reduction Units (ERU) from Clean Development Mechanism and Joint Implementation (JI), respectively (see Daskalakis, Ibikunle, and Diaz-Rainey 2011).
2. We also use the tick rule algorithm (see Lee and Ready 1991), with comparable results.
3. For robustness, we consider analysis based on volume-weighted price impact measures in order to eliminate some of the noise in the data, if indeed this was prominent. We find that the results are quantitatively similar. The major reason for this is that approximately 90% of the block trades are in the 50,000-100,000 EUAs size category, thus the trades mainly have a similar multiplying factor.
4. We also use the plain number of instruments traded, the natural logarithm of the Euro value of the block trades, the instrument volume relative to the average daily instrument volume, and the Euro value relative to the average daily trading Euro value. As is the case with Frino, Jarnecic, and Lepone (2007), the natural logarithm of the number of instruments traded provides the best fit.
5. We also use standard deviation of the execution price of trades, in line with Alzahrani et al. (2013). The results are quantitatively similar.

6. We also use open interest on its own as a measure of liquidity; however, the results obtained are less significant across all the models.
7. The expectation is for higher levels of volatility to lead to higher block trade price impact. Thus, block purchases will induce positively skewed price impact and sell block trades will induce negative price impact when the market becomes relatively more volatile.
8. We also divide the trading day into three intervals, in line with previous studies, in order to test the intraday period dependencies. The results are qualitatively similar.

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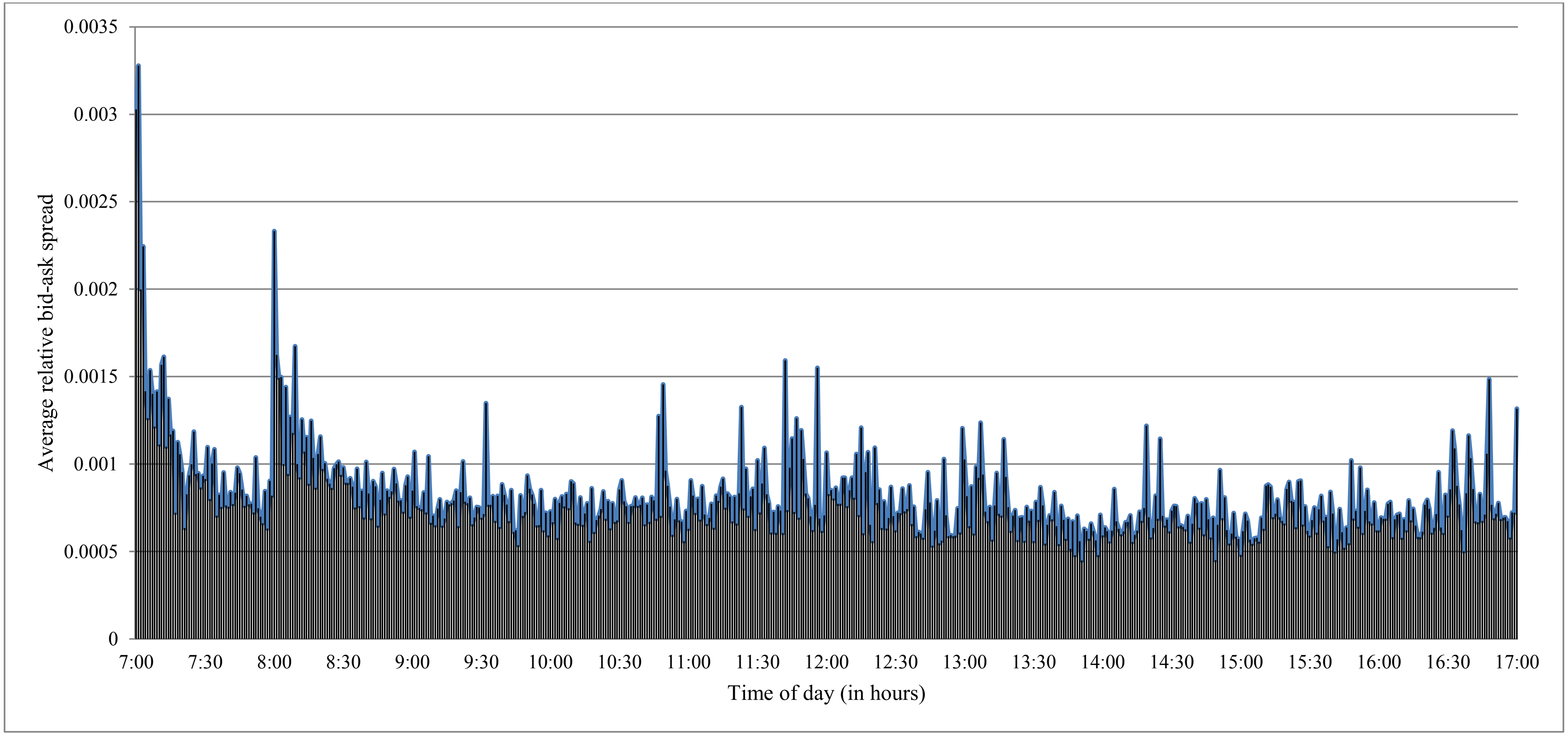
Figure 1

Intraday Variations in Relative Bid-ask Spread on the ECX



Note: The figure shows the prevailing intraday relative bid-ask spread pattern for all trades of December maturity EUA Futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. Average bid-ask spread, which is defined for each trade as the last ask price prior to the trade minus the last bid price before the trade, divided by the average of both prices, is computed for each of the six EUA Futures contracts in our sample and then averaged cross-sectionally across all contracts.

Table 1

Panel A Summary Statistics for Block Trades

	Number of trades	Average number of contracts/trade	% of total number of trades	Average transaction value/trade (€'000)	Average Relative Spread (%)	Standard deviation (%)
All trades	961,131	6.79		108.40	0.07	
Block trades	16,715	78.94	1.74	1,232.71	0.06	0.47
Block purchases	8,356	80.21	0.87	1,258.03	0.07	0.58
Block sales	8,359	77.67	0.87	1,207.40	0.06	0.30

Panel B: Correlation Matrix for Determinants

	BAS	Market Return	Momentum	Volatility	Size	Turnover
BAS	1					
Market Return	-0.017	1				
Momentum	-0.023	0.261	1			
Volatility	0.322	0.001	-0.041	1		
Size	-0.012	0.016	-0.002	-0.019	1	
Turnover	-0.080	0.076	0.152	-0.257	0.006	1

Note: Panel A shows descriptive statistics for block trades of December maturity EUA futures executed on the European Climate Exchange (ECX) platform between January 2008 and April 2012. Panel B shows the correlation matrix of the determinants of price impact of block trades, the determinants/variables are as defined in Table 2.

Table 2

Determinants of Price Impact of Block Trades

	Permanent effects			Total effects			Temporary effects		
	All	Purchase	Sell	All	Purchase	Sell	All	Purchase	Sell
Variables									
Size	-3.25E-05 (1.74E-05)	-1.47E-05 (2.59E-05)	-0.0004*** (0.0002)	-1.78E-05 (1.04E-05)	0.0004*** (0.0001)	-0.0002** (9.84E-05)	-1.34E-05 (1.73E-05)	-2.68E-05 (2.65E-05)	0.0001*** (1.17E-05)
Volatility	0.1820* (0.0944)	0.0817 (0.1318)	0.0399** (0.0188)	0.0317 (0.1201)	-0.0417** (0.0200)	0.0285*** (0.0080)	0.0735** (0.0377)	0.1396*** (0.0391)	-0.0109 (0.0673)
Turnover	-0.0733 (0.1367)	-0.0740 (0.2075)	-0.1817*** (0.0552)	-0.1357* (0.0801)	-0.2657** (0.1211)	0.0340 (0.0946)	0.0530*** (0.0129)	0.1730* (0.0944)	-0.1158*** (0.0193)
Market Return	0.0157*** (0.0060)	0.0102 (0.0099)	0.0174*** (0.0054)	-0.0147*** (0.0046)	-0.0248*** (0.0080)	0.0124*** (0.0032)	0.0204*** (0.0070)	0.0350*** (0.0124)	0.0150*** (0.0049)
Momentum	-0.0031 (0.0020)	-0.0041* (0.0025)	-0.0020 (0.0023)	-0.0028** (0.0013)	-0.0040*** (0.0015)	-0.0016** (0.0013)	-0.0005 (0.0025)	-0.0003 (0.0040)	-0.0004 (0.0019)
BAS	-0.08107 (0.0641)	-0.0833 (0.0544)	0.0649** (0.0306)	-0.1994** (0.0924)	-0.1006*** (0.0415)	0.1318*** (0.0370)	0.0273 (0.0946)	0.1291 (0.1266)	0.0319 (0.0770)
TD_1	0.0004 (0.0005)	0.0004 (0.0009)	0.0003 (0.0003)	-9.53E-06 (0.0002)	-0.0006* (0.0003)	0.0003* (0.0002)	0.0004 (0.0005)	0.0009 (0.0010)	5.45E-05 (0.0002)
TD_2	0.0006 (0.0005)	0.0012 (0.0010)	-2.74E-05 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)	-8.88E-05 (0.0001)	0.0008 (0.0005)	0.0014 (0.0010)	6.17E-05 (0.0002)
TD_3	0.0006 (0.0005)	0.0010 (0.0009)	0.0002 (0.0003)	-7.30E-05 (0.0002)	-0.0003 (0.0003)	9.91E-05 (0.0001)	0.0007 (0.0005)	0.0012 (0.0009)	0.0001 (0.0002)
TD_4	0.0006 (0.0005)	0.0011 (0.0009)	5.40E-05 (0.0002)	-0.0002 (0.0002)	-0.0005* (0.0003)	0.0001 (0.0001)	0.0008 (0.0005)	0.0016* (0.0009)	-5.84E-05 (0.0002)
TD_5	0.0002 (0.0005)	0.0008 (0.0009)	-0.0005** (0.0003)	-0.0005*** (0.0002)	-0.0008*** (0.0003)	-0.0003** (0.0001)	0.0006 (0.0005)	0.0016* (0.0009)	-0.0002 (0.0002)
TD_6	0.0008* (0.0005)	0.0013 (0.0009)	0.0004 (0.0003)	0.0003 (0.0003)	0.0003 (0.0005)	0.0003* (0.0002)	0.0005 (0.0005)	0.0010 (0.0010)	9.21E-05 (0.0002)

TD_7	0.0007	0.0012	0.0001	-0.0002	-0.0005	7.00E-05	0.0009*	0.0017	7.43E-05
	(0.0005)	(0.0009)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0005)	(0.0009)	(0.0002)
TD_8	0.0002	0.0007	-0.0005*	-0.0003**	-0.0004*	-0.0003**	0.0005	0.0011	-0.0002
	(0.0005)	(0.0009)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0009)	(0.0002)
TD_9	0.0005	0.0010	-0.0001	-0.0003**	-0.0004**	-0.0002	0.0007	0.0013	8.75E-05
	(0.0005)	(0.0009)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0009)	(0.0002)
DD_1	5.48E-05	-0.0002	0.00023	-0.0002	-0.0004*	3.21E-05	0.0002	0.0003	0.0002
	(0.0005)	(0.0010)	(0.0003)	(0.0002)	(0.0003)	(0.0001)	(0.0005)	(0.0010)	(0.0002)
DD_2	0.0003	0.0005	2.96E-05	-0.0002*	-0.0004	-0.0001	0.0005	0.0009	0.0002
	(0.0004)	(0.0008)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0008)	(0.0002)
DD_3	0.0004	0.0007	7.64E-05	0.0001	7.70E-05	0.0001	0.0003	0.0007	-4.50E-05
	(0.0004)	(0.0008)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0004)	(0.0008)	(0.0002)
DD_4	0.0001	0.0004	-0.0003	-0.0002*	-0.0002**	-4.31E-05	0.0003	0.0009	-0.0002
	(0.0004)	(0.0008)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(0.0008)	(0.0002)
MD_1	0.0005	0.0003	0.0007**	0.0005***	0.0003	0.0008***	-1.76E-05	5.21E-05	-9.67E-05
	(0.0003)	(0.0006)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0003)
MD_2	0.0007**	0.0005	0.0009***	0.0006***	0.0007	0.0006***	6.07E-05	-0.0002	0.0003
	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0005)	(0.0002)	(0.0003)	(0.0005)	(0.0003)
MD_3	0.0005*	0.0002	0.0008**	0.0002	-7.33E-05	0.0005**	0.0003	0.0002	0.0003
	(0.0003)	(0.0005)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0003)
MD_4	-8.85E-06	-0.0006	0.0007**	0.0003*	8.71E-05	0.0006***	-0.0003	-0.0007	8.85E-05
	(0.0007)	(0.0013)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0007)	(0.0013)	(0.0003)
MD_5	-8.92E-05	-0.0005	0.0004	0.0002	-8.97E-05	0.0005**	-0.0003	-0.0004	-0.0001
	(0.0003)	(0.0005)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0003)
MD_6	0.0007**	0.0005	0.0010***	0.0006***	0.0004	0.0008***	0.0002	0.0001	0.0002
	(0.0003)	(0.0005)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0003)
MD_7	0.0007*	0.0001	0.0013***	0.0003	-0.0001	0.0008***	0.0004	0.0003	0.0005*
	(0.0004)	(0.0005)	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0005)	(0.0003)
MD_8	0.0005	0.0006	0.0005	0.0004**	0.0003	0.0006***	0.0001	0.0003	-0.0001
	(0.0004)	(0.0005)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0005)	(0.0004)
MD_9	0.0004	0.0004	0.0005*	0.0004*	0.0003	0.0006***	2.49E-05	0.0002	-8.87E-05
	(0.0003)	(0.0005)	(0.0003)	(0.0002)	(0.0005)	(0.0002)	(0.0003)	(0.0005)	(0.0003)

MD_{10}	0.0004 (0.0004)	0.0002 (0.0005)	0.0005 (0.0004)	0.0002 (0.0002)	-6.68E-06 (0.0003)	0.0004* (0.0002)	0.0002 (0.0003)	0.0002 (0.0005)	7.57E-05 (0.0003)
MD_{11}	-0.0004 (0.0007)	-0.0011 (0.0013)	0.0006* (0.0003)	0.0003 (0.0002)	0.0002 (0.0003)	0.0005** (0.0002)	-0.0007 (0.0007)	-0.0013 (0.0005)	8.02E-05 (0.0003)
Constant	-0.001 (0.0007)	-0.0018 (0.0013)	-0.0002 (0.0004)	-0.0001 (0.0003)	-1.25E-05 (0.0005)	-0.0002 (0.0002)	-0.0010 (0.0007)	-0.0019 (0.0014)	4.32E-05 (0.0003)
Observations	16715	8356	8359	16715	8356	8359	16715	8356	8359
R-squared	0.0022	0.0024	0.0230	0.0072	0.0218	0.0269	0.0026	0.0044	0.0081

Note: The table reports regression results for all purchase and sell block trades of December maturity EUA futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The coefficients are reported along with the standard errors (in parenthesis). The following regression is estimated using OLS with Newey and West (1987) heteroscedastic and autocorrelation consistent covariance matrix:

$$PI_t = \gamma_0 + \gamma_x X_t + \gamma_2 \sum_{i=1}^{9} TD_i + \gamma_3 \sum_{i=1}^{4} DD_i + \gamma_4 \sum_{i=1}^{11} MD_i + \varepsilon_t$$

where PI_t corresponds to one of three price impact measures: total price impact, permanent price impact and temporary price impact. The explanatory variables are computed as follows. $\boldsymbol{X}_t$ is a vector of six explanatory variables (Size, Volatility, Turnover, Marketreturn, Momentum and BAS) defined below. TD_i, DD_i and MD_i are dummy variables for time (hour) of day, day of week and month of year and are further defined below. Size represents the natural logarithm of the number of December maturity futures contracts for each block trade; Volatility is the standard deviation of trade to trade returns prior to the block trade on the trading day; Turnover is the natural logarithm of the futures contracts turnover on the trading day prior to the block trade, turnover is the ratio of total trade volume prior to the block to the prevailing open interest estimates; Marketreturn is the return of EUA Futures contract specific index computed by the ECX; Momentum corresponds to the cumulative return on the specific EUA Futures contract in the five days prior to the block trade; BAS is the prevailing relative bid-ask spread at the time the block trade is executed, BAS is measured as the last ask price prior to the block trade minus the last bid price before the block trade, divided by the average of both prices. TD_1 to TD_9 equal 1 if the block trade occurs in any of the corresponding hour of trade from the first hour (1) to the ninth hour (9) of the trading day, and 0 otherwise. DD_1 to DD_4 equal 1 if the block trade occurs in any of the corresponding day of the week from Monday (1) to Thursday (4) of the trading week, and 0 otherwise. Any of MD_1 to MD_{11} equals 1 if the block trade occurs in any of the corresponding months of the year from January (1) to November (11) and 0 otherwise. One EUA Futures contract has an underlying of 1,000 EUAs. ***, **, * indicate statistical significance at 1%, 5% and 10% level respectively.

Table 3

Determinants of Price Impact and Block Trade Sizes (Purchases)

	Permanent effects			Total effects			Temporary effects		
	50-100	101-200	>200	50-100	101-200	>200	50-100	101-200	>200
% Proportion	(89.92%)	(6.63%)	(3.45%)	(89.92%)	(6.63%)	(3.45%)	(89.92%)	(6.63%)	(3.45%)
Variables									
Size	8.40E-06	4.01E-05	2.38E-06	-5.37E-08	2.86E-06	4.81E-06**	8.83E-06	3.81E-05	-2.35E-06
	(8.88E-06)	(2.90E-05)	(1.73E-06)	(3.82E-06)	(1.08E-05)	(2.11E-06)	(8.56E-06)	(3.02E-05)	(2.10E-06)
Volatility	0.0455	1.1161***	-0.2610	-1.0946***	1.4354**	-1.0247***	0.1881	-0.2271	-0.0372
	(0.1515)	(0.4051)	(0.2120)	(0.2200)	(0.6454)	(0.3711)	(0.2073)	(0.7360)	(0.4340)
Turnover	-0.1514	-0.6615	0.0529	-0.3513	-0.3675	-0.2470**	0.1578	-0.3157	0.2986
	(0.4487)	(0.6125)	(0.1749)	(0.2838)	(0.3304)	(0.1228)	(0.4527)	(0.5964)	(0.1260)
Market Return	0.0179**	-0.0810	0.0226*	0.0212***	-0.0749**	0.0002	0.0394***	-0.0089	0.0221
	(0.0077)	(0.0971)	(0.0140)	(0.0080)	(0.0378)	(0.0253)	(0.0107)	(0.1006)	(0.0284)
Momentum	-0.0043*	-0.0379	-0.0133*	-0.0066**	0.0385***	-0.0279***	0.0028	-0.0743**	0.0136
	(0.0026)	(0.0305)	(0.0073)	(0.0033)	(0.0112)	(0.0117)	(0.0040)	(0.0349)	(0.0200)
BAS	-0.0547	-1.1884	-0.1837	-0.2725**	-0.4582**	-0.0021	0.0310	-0.7479	-0.1882
	(0.0529)	(0.9621)	(0.3443)	(0.1193)	(0.2073)	(0.2804)	(0.1297)	(0.9649)	(0.4088)
TD_1	-0.0002	0.0078	-0.0006	-0.0005*	-0.0018	0.0009	0.0003	0.0095	-0.0016
	(0.0008)	(0.0087)	(0.0027)	(0.0003)	(0.0012)	(0.0033)	(0.0009)	(0.0086)	(0.0030)
TD_2	0.0005	0.0090	0.0017	-0.0003	0.0005	0.0002	0.0008	0.0085	0.0015
	(0.0007)	(0.0091)	(0.0015)	(0.0002)	(0.0010)	(0.0008)	(0.0008)	(0.0091)	(0.0014)
TD_3	0.0004	0.0082	0.0012	-0.0003	-0.0007	0.0002	0.0006	0.0089	0.0009
	(0.0008)	(0.0072)	(0.0010)	(0.0003)	(0.0013)	(0.0012)	(0.0008)	(0.0074)	(0.0016)
TD_4	0.0005	0.0101	0.0011	-0.0005*	-0.0007	9.27E-05	0.0010	0.0108	0.0010
	(0.0008)	(0.0092)	(0.0010)	(0.0003)	(0.0011)	(0.0010)	(0.0008)	(0.0093)	(0.0013)
TD_5	0.0002	0.0093	0.0020*	-0.0010***	-0.0004	0.0010	0.0012	0.0096	0.0011
	(0.0008)	(0.0090)	(0.0011)	(0.0003)	(0.0010)	(0.0011)	(0.0008)	(0.0090)	(0.0012)
TD_6	0.0006	0.0089	0.0014	0.0002	8.21E-05	0.0043**	0.0005	0.0088	-0.0029
	(0.0008)	(0.0084)	(0.0012)	(0.0006)	(0.0011)	(0.0022)	(0.0009)	(0.0085)	(0.0025)

TD_7	0.0006 (0.0007)	0.0097 (0.0087)	0.0013 (0.0013)	-0.0005* (0.0003)	-7.63E-06 (0.0007)	0.0002 (0.0010)	0.0011 (0.0008)	0.0096 (0.0087)	0.0011 (0.0016)
TD_8	3.02E-05 (0.0007)	0.0089 (0.0078)	0.0020** (0.0009)	-0.0005** (0.0002)	0.0005 (0.0008)	0.0015 (0.0012)	0.0005 (0.0007)	0.0084 (0.0078)	0.0004 (0.0013)
TD_9	0.0003 (0.0007)	0.0075 (0.0070)	0.0025* (0.0014)	-0.0004** (0.0002)	-0.0004 (0.0008)	-0.0001 (0.0011)	0.0007 (0.0007)	0.0078 (0.0071)	0.0026 (0.0014)
DD_1	0.0006 (0.0009)	-0.0114 (0.0108)	-0.0020* (0.0011)	-0.0005 (0.0003)	0.0001 (0.0017)	-0.0024 (0.0015)	0.0011 (0.0009)	-0.0114 (0.0110)	0.0003 (0.0016)
DD_2	0.0006 (0.0009)	0.0012 (0.0016)	-0.0006 (0.0013)	-0.0004* (0.0002)	-2.42E-06 (0.0008)	-0.0014 (0.0012)	0.0010 (0.0009)	0.0012 (0.0018)	0.0007 (0.0017)
DD_3	0.0008 (0.0009)	0.00154 (0.0013)	-0.0016 (0.0013)	0.0002 (0.0003)	-0.0004 (0.0008)	-0.0019 (0.0014)	0.0007 (0.0009)	0.0019 (0.0015)	0.0002 (0.0020)
DD_4	0.0005 (0.0009)	0.0003 (0.0012)	-0.0014 (0.0012)	-0.0003 (0.0002)	-0.0012 (0.0008)	-0.0023* (0.0012)	0.0008 (0.0009)	0.0015 (0.0014)	0.0008 (0.0016)
MD_1	0.0003 (0.0006)	0.0002 (0.0021)	0.0015 (0.0010)	0.0002 (0.0004)	-0.0015 (0.0011)	0.0010 (0.0007)	7.93E-05 (0.0006)	0.0016 (0.0021)	0.0005 (0.0011)
MD_2	0.0004 (0.0005)	0.0023 (0.0026)	-0.0006 (0.0009)	0.0006 (0.0005)	0.0024 (0.0022)	0.0021 (0.0018)	-0.0001 (0.0006)	0.0002 (0.0032)	-0.0026 (0.0023)
MD_3	-7.77E-05 (0.0005)	0.0042 (0.0029)	0.0010 (0.0007)	-6.88E-05 (0.0004)	0.0004 (0.0010)	-0.0010 (0.0012)	-1.04E-06 (0.0005)	0.0038 (0.0028)	0.0020 (0.0015)
MD_4	-0.0009 (0.0014)	0.0021 (0.0022)	0.0007 (0.0008)	-7.69E-05 (0.0004)	0.0001 (0.0011)	0.0014 (0.0010)	-0.0008 (0.0014)	0.0021 (0.0021)	-0.0006 (0.0010)
MD_5	-0.0004 (0.0005)	-0.0008 (0.0021)	-0.0018 (0.0012)	-0.0002 (0.0004)	0.0003 (0.0011)	-0.0005 (0.0010)	-0.0002 (0.0005)	-0.0010 (0.0021)	-0.0013 (0.0019)
MD_6	0.0004 (0.0005)	0.0011 (0.0024)	-0.0005 (0.0010)	0.0003 (0.0004)	-9.19E-07 (0.0010)	0.0011 (0.0016)	0.0001 (0.0005)	0.0011 (0.0025)	-0.0016 (0.0014)
MD_7	6.23E-05 (0.0005)	0.0012 (0.0019)	0.0006 (0.0014)	-0.0002 (0.0004)	0.0011 (0.0011)	-0.0015 (0.0026)	0.0003 (0.0006)	0.0002 (0.0020)	0.0021 (0.0019)
MD_8	0.0004 (0.0005)	0.0024 (0.0028)	0.0035*** (0.0013)	0.0003 (0.0004)	-0.0011 (0.0011)	0.0004 (0.0014)	2.14E-05 (0.0006)	0.0035 (0.0026)	0.0032 (0.0021)
MD_9	0.0004 (0.0005)	0.0017 (0.0021)	0.0012 (0.0008)	8.08E-05 (0.0005)	0.0003 (0.0018)	0.0025 (0.0020)	0.0003 (0.0006)	0.0015 (0.0030)	-0.0013 (0.0017)

MD_{10}	0.0002	-0.0014	0.0007	2.79E-05	-0.0010	-0.0007	0.0002	-0.0003	0.0013
	(0.0005)	(0.0028)	(0.0011)	(0.0004)	(0.0014)	(0.0012)	(0.0005)	(0.0030)	(0.0015)
MD_{11}	0.0001	-0.0147	-0.0010	0.0001	0.0004	-0.0005	-3.26E-05	-0.0151	-0.0006
	(0.0005)	(0.0159)	(0.0009)	(0.0004)	(0.0013)	(0.0007)	(0.0005)	(0.0161)	(0.0011)
Constant	-0.0018	-0.0136	-0.0019	0.0007	-0.0013	0.0020	-0.0023	-0.0126	-0.0013
	(0.0017)	(0.0095)	(0.0018)	(0.0006)	(0.0012)	(0.0020)	(0.0018)	(0.0096)	(0.0024)
Observations	7514	554	288	7514	554	288	7514	554	288
R-squared	0.0027	0.0363	0.1646	0.0232	0.2208	0.2484	0.0066	0.0359	0.1901

Note: The table reports regression results for all purchase block trades of December maturity EUA futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The coefficients are reported along with the standard errors (in parenthesis). The following regression is estimated using OLS with Newey and West (1987) heteroscedastic and autocorrelation consistent covariance matrix:

$$PI_t = \gamma_0 + \gamma_x X_t + \gamma_2 \sum_{i=1}^{9} TD_i + \gamma_3 \sum_{i=1}^{4} DD_i + \gamma_4 \sum_{i=1}^{11} MD_i + \varepsilon_t$$

All variables are as defined in Table 2. ***, **, * indicate statistical significance at 1%, 5% and 10% level respectively.

Table 4

Determinants of Price Impact and Block Trade Sizes (Sales)

	Permanent effects			Total effects			Temporary effects		
	50-100	101-200	>200	50-100	101-200	>200	50-100	101-200	>200
% Proportion	(90.85%)	(5.91%)	(3.24%)	(90.85%)	(5.91%)	(3.24%)	(90.85%)	(5.91%)	(3.24%)
Variables									
Size	-1.62E-05***	1.36E-06	-3.91E-07	-4.26E-06**	-1.23E-07	-2.09E-06**	-1.99E-06	1.50E-06	1.71E-06
	(4.32E-06)	(5.83E-06)	(1.41E-06)	(2.04E-06)	(3.09E-06)	(9.42E-07)	(3.48E-06)	(4.36E-06)	(1.22E-06)
Volatility	0.0426	0.1953	0.1486	0.2091**	0.4329**	-0.4295*	0.0330	-0.2366***	0.5814**
	(0.1167)	(0.2846)	(0.2211)	(0.0920)	(0.2094)	(0.2576)	(0.0698)	(0.0819)	(0.2700)
Turnover	-0.0020	-0.0099	0.0010	0.0668	-0.1157	0.0682	-0.2682***	0.0166	-0.0680
	(0.0033)	(0.0037)	(0.0116)	(0.1994)	(0.2193)	(0.0525)	(0.0432)	(0.2173)	(0.1013)
Market Return	0.0182***	0.0158	0.0083	0.0125***	0.0059	0.0247***	0.0057	0.0099	-0.0165*
	(0.0058)	(0.0119)	(0.0096)	(0.0033)	(0.0076)	(0.0060)	(0.0053)	(0.0086)	(0.0095)
Momentum	-0.0013	-0.0063	-0.0222***	-0.0012	-0.0012	-0.0111***	-9.88E-06	-0.0051	-0.0111**
	(0.0025)	(0.0056)	(0.0062)	(0.0013)	(0.0027)	(0.0038)	(0.0021)	(0.0047)	(0.0048)
BAS	0.2873**	-0.3524***	0.2609	0.1548	-0.3334***	0.1578	0.0314	-0.0203	0.1044
	(0.1394)	(0.1290)	(0.3387)	(0.1082)	(0.0935)	(0.3322)	(0.0810)	(0.1322)	(0.1159)
TD_1	0.0003	0.0007	-0.0018	0.0003*	0.0003	-0.0018*	-1.39E-05	0.0004	-7.10E-06
	(0.0003)	(0.0005)	(0.0012)	(0.0002)	(0.0004)	(0.0010)	(0.0003)	(0.0003)	(0.0007)
TD_2	-0.0001	0.0008	-0.0003	-0.0001	0.0007	-0.0004	2.58E-05	6.38E-05	8.66E-05
	(0.0003)	(0.0006)	(0.0009)	(0.0002)	(0.0005)	(0.0006)	(0.0002)	(0.0004)	(0.0009)
TD_3	0.0002	0.0005	-0.0007	9.14E-05	0.0002	-0.0008**	7.98E-05	0.0003	9.35E-05
	(0.0003)	(0.0008)	(0.0008)	(0.0002)	(0.0004)	(0.0004)	(0.0002)	(0.0006)	(0.0006)
TD_4	-7.15E-05	0.0007	0.0012*	5.55E-05	0.0003	0.0004	-0.0001	0.0004	0.0008
	(0.0003)	(0.0006)	(0.0007)	(0.0002)	(0.0004)	(0.0005)	(0.0002)	(0.0004)	(0.0005)
TD_5	-0.0006**	0.0004	0.0004	-0.0003**	0.0004	-8.39E-05	-0.0003	-2.58E-05	0.0004
	(0.0003)	(0.0006)	(0.0007)	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0005)	(0.0006)
TD_6	0.0004	0.0002	0.0014**	0.0003*	0.0002	0.0003	6.38E-05	7.78E-06	0.0011*
	(0.0003)	(0.0006)	(0.0007)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0005)	(0.0006)

TD_7	8.43E-05 (0.0003)	-0.0001 (0.0005)	0.0016** (0.0008)	3.77E-05 (0.0001)	0.00012 (0.0004)	0.0004 (0.0004)	4.75E-05 (0.0002)	-0.0003 (0.0004)	0.0012 (0.0008)
TD_8	-0.0005** (0.0003)	-0.0006 (0.0006)	0.0013 (0.0009)	-0.0003** (0.0001)	-0.0003 (0.0003)	0.0003 (0.0006)	-0.0002 (0.0002)	-0.0003 (0.0005)	0.0011* (0.0006)
TD_9	-0.0003 (0.0003)	0.0008 (0.0005)	0.0020** (0.0008)	-0.0003** (0.0001)	0.0001 (0.0004)	0.0003 (0.0006)	-1.59E-05 (0.0002)	0.0007* (0.0004)	0.0017*** (0.0006)
DD_1	0.0003 (0.0003)	-0.0001 (0.0005)	5.54E-05 (0.0007)	4.61E-05 (0.0001)	0.0002 (0.0004)	-0.0011** (0.0005)	0.0002 (0.0002)	-0.0003 (0.0004)	0.0011* (0.0006)
DD_2	0.0001 (0.0003)	-0.0013*** (0.0004)	6.51E-05 (0.0006)	-8.76E-05 (0.0001)	-0.0003 (0.0003)	-0.0010** (0.0004)	0.0002 (0.0002)	-0.0010 (0.0003)	0.0010* (0.0006)
DD_3	0.0001 (0.0002)	3.57E-05 (0.0005)	-9.30E-05 (0.0007)	0.0002 (0.0001)	0.0002 (0.0003)	-0.0006 (0.0005)	-3.55E-05 (0.0002)	-0.0002 (0.0004)	0.0005 (0.0005)
DD_4	-0.0002 (0.0002)	-0.0010** (0.0004)	-0.0006 (0.0007)	2.06E-05 (0.0001)	-0.0005 (0.0003)	-0.0011*** (0.0004)	-0.0002 (0.0002)	-0.0005 (0.0004)	0.0005 (0.0006)
MD_1	0.0006* (0.0004)	0.0007 (0.0006)	0.0030** (0.0013)	0.0008*** (0.0002)	0.0002 (0.0004)	0.0015** (0.0007)	-0.0002 (0.0003)	0.0004 (0.0004)	0.0015* (0.0009)
MD_2	0.0009** (0.0004)	3.06E-05 (0.0006)	0.0032*** (0.0012)	0.0007*** (0.0002)	0.0003 (0.0004)	0.0009 (0.0006)	0.0003 (0.0003)	-0.0003 (0.0004)	0.0023*** (0.0008)
MD_3	0.0007* (0.0003)	5.19E-05 (0.0006)	0.0036*** (0.0010)	0.0005** (0.0002)	2.42E-05 (0.0004)	0.0016** (0.0006)	0.0002 (0.0003)	2.68E-05 (0.0004)	0.0020*** (0.0007)
MD_4	0.0006* (0.0003)	0.0008 (0.0008)	0.0029** (0.0011)	0.0006*** (0.0002)	0.0007 (0.0005)	0.0019*** (0.0007)	1.87E-05 (0.0003)	0.0001 (0.0005)	0.0010 (0.0007)
MD_5	0.0003 (0.0004)	-0.0001 (0.0006)	0.0023** (0.0010)	0.0005** (0.0003)	-0.0003 (0.0003)	0.0023*** (0.0007)	-0.0002 (0.0003)	0.0001 (0.0004)	9.29E-05 (0.0006)
MD_6	0.0010** (0.0004)	0.0006 (0.0006)	0.0024* (0.0013)	0.0008*** (0.0003)	0.0004 (0.0004)	0.0012 (0.0008)	0.0002 (0.0003)	0.0002 (0.0005)	0.0011* (0.0007)
MD_7	0.0013*** (0.0004)	-1.44E-05 (0.0007)	0.0023* (0.0013)	0.0008*** (0.0003)	3.80E-05 (0.0004)	0.0016** (0.0008)	0.0005 (0.0003)	-5.16E-05 (0.0006)	0.0006 (0.0009)
MD_8	0.0002 (0.0004)	0.0009 (0.0008)	0.0054*** (0.0016)	0.0005** (0.0002)	0.0009 (0.0006)	0.0027*** (0.0008)	-0.0003 (0.0004)	5.79E-05 (0.0005)	0.0027*** (0.0010)
MD_9	0.0005 (0.0003)	-0.0005 (0.0013)	0.0029*** (0.0010)	0.0007*** (0.0002)	-0.0003 (0.0004)	0.0007 (0.0007)	-0.0002 (0.0003)	-0.0001 (0.0010)	0.0022*** (0.0006)

MD_{10}	0.0005 (0.0005)	-0.0009 (0.0010)	0.0026*** (0.0009)	0.0005* (0.0003)	-0.0003 (0.0005)	0.0010** (0.0006)	4.53E-05 (0.0003)	-0.0006 (0.0007)	0.0016*** (0.0006)
MD_{11}	0.0005 (0.0003)	0.0001 (0.0006)	0.0031*** (0.0010)	0.0005** (0.0002)	0.0001 (0.0004)	0.0009* (0.0006)	-3.50E-05 (0.0003)	-4.21E-06 (0.0004)	0.0022*** (0.0006)
Constant	0.0003 (0.0005)	0.0001 (0.0010)	-0.0034*** (0.0011)	-6.20E-05 (0.0003)	-7.09E-05 (0.0006)	0.0005 (0.0007)	0.0003 (0.0004)	0.0002 (0.0007)	-0.0039*** (0.0008)
Observations	7594	494	271	7594	494	271	7594	494	271
R-squared	0.0228	0.0857	0.2089	0.0289	0.1342	0.2517	0.0102	0.0613	0.2467

Note: The table reports regression results for sell block trades of December maturity EUA futures contracts executed on the European Climate Exchange (ECX) platform between January 2008 and April 2011. The coefficients are reported along with the standard errors (in parenthesis). The following regression is estimated using OLS with Newey and West (1987) heteroscedastic and autocorrelation consistent covariance matrix:

$$PI_t = \gamma_0 + \gamma_x X_t + \gamma_2 \sum_{i=1}^{9} TD_i + \gamma_3 \sum_{i=1}^{4} DD_i + \gamma_4 \sum_{i=1}^{11} MD_i + \varepsilon_t$$

All variables are as defined in Table 2. ***, **, * indicate statistical significance at 1%, 5% and 10% level respectively.